

The implementation of an optimized neural network in a hybrid system for energy management

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ABSTRACT

In the face of increasing global energy demand and volatile energy prices, many countries are searching for solutions to ensure their energy independence. One of the most popular solutions is to incorporate renewable energy sources in their energy systems. While there are many advantages to integrating renewable energy sources, it is important to note that their intermittent operation can present challenges. Energy storage and smart grid management systems are key solutions to overcome these challenges and ensure sustainable, reliable use of renewable energy sources. In this article, we present an intelligent electrical energy management system for hybrid energy systems. This management system is based on a multi-layer neural network that has undergone an architecture optimization phase to improve the accuracy of real-time energy management and simplify its implementation. The management model that was built demonstrated highly good performance across a range of test circumstances.

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1. INTRODUCTION

In the energy context, the challenges of climate change, depleting fossil energy reserves and energy independence have encouraged the development of alternative solutions for the production, distribution and storage of energy. The integration of these energy solutions into the power grid has led to the emergence of concepts such as smart grids, decentralized production and hybridization of sources [1], [2]. The latter involves combining different energy sources, like photovoltaic panels and wind turbines, generators and storage units, to provide a stable, reliable power supply and improve the balance of the electrical system. However, despite the many economic and environmental benefits of using renewable energy sources, these sources can be subject to significant variations due to their direct correlation with meteorological conditions. This can make it difficult to provide a constant, reliable power supply, leading to service interruptions and breakdowns in energy production. These interruptions can have a major impact on critical loads such as data centers, hospitals and industrial facilities, causing damage, data loss and even risks to personal safety. In order to solve these

problems, it is crucial to use intelligent energy management techniques and to put in place energy storage systems and secondary energy sources to compensate for fluctuations [3], [4].

This paper presents an intelligent energy management system for hybrid systems using artificial neural networks. The hybrid system consists of renewable energy sources, a storage unit, a power generator, critical and non-critical loads and a public network link. The latter is used in emergencies when locally-generated energy is insufficient to supply the loads. The management system is a multi-layer neural network undergoing an architecture optimization phase, in which a variety of multi-layer neural network learning tools and algorithms are used. The neural network optimization phase is essential to build an energy management model with a minimum number of components and to facilitate their implementation in hardware. The work is divided into three parts: the architecture of the system studied and the management strategy; discussion of the results and validation of the management model; and finally, the conclusion, which summarizes the work accomplished.

2. SYSTEM ARCHITECTURE

This part of the article is divided into two sections. The first describes the architecture and components of the hybrid system under study. The second presents the energy management model based on an artificial neural network, as well as its inputs and outputs.

2.1. Components and roles

A hybrid energy system combines different energy sources and conversion technologies to supply local consumers and inject surplus energy into the public grid. They can operate autonomously or be connected to the grid [5]. Among the renewable energy sources most frequently used in hybrid systems are wind turbines and photovoltaic panels. Due to the intermittency of the photovoltaic system, which is dependent on weather conditions, the presence of critical loads and variable energy demand from consumers, the integration of other energy sources has become a necessity [6], [7]. Figure 1 shows the components of the system studied, comprising a photovoltaic generator with maximum power point tracking or MPPT charge controller [8], [9], a power generator, a battery [10], and a connection to the public grid. The loads are divided into two categories: critical loads (1 and 2) continuously connected to the grid and non-critical loads (3 and 4) connected randomly, resulting in variable energy demand. The system integrates direct current or DC/DC, DC/ alternating current or AC and AC/DC converters for energy conversion, as well as switches to control the connections of energy sources and loads.

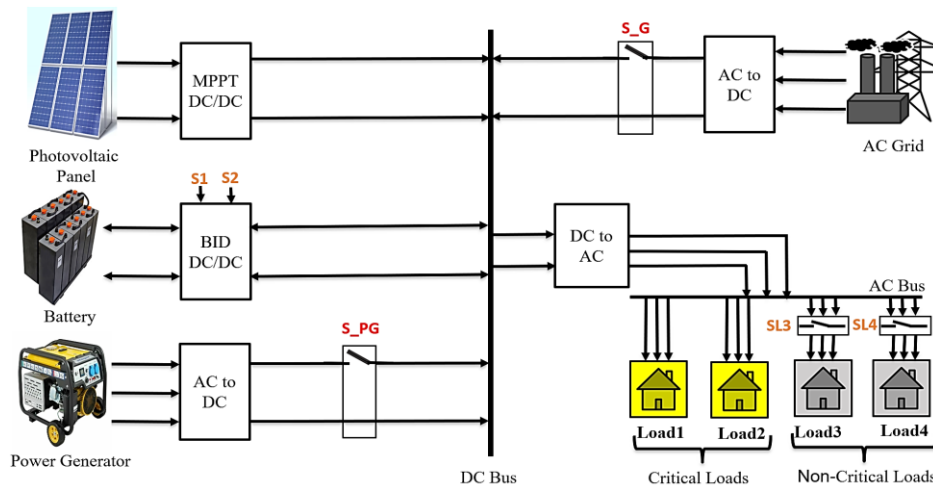


Figure 1. Architecture of the system studied

2.2. Energy management system

In hybrid energy systems, the variability of the power generated by the photovoltaic panels, the variability of the power demanded by the load system and the presence of critical loads requiring uninterrupted power supply are critical points to consider [11]–[14]. To guarantee a stable, reliable power supply, it's essential to integrate an intelligent energy management system. This system effectively supervises and manages energy production and consumption in real time, adjusting the power delivered by the various energy sources to meet

consumers' needs. In addition, this energy management system protects batteries against overloads and deep discharges, prolonging their service life, and ensuring their optimal operation.

As shown in Figure 2, The management model used in this study is based on a multilayer neural network. Its inputs include the power generated by the photovoltaic array, the power required by the loads, the battery state-of-charge, and the indicator of the operation of the array. The latter is a binary parameter indicating the status of the power generator. The model's outputs are switches S1 and S2. These two switches play a crucial role in controlling the battery's state of charge. Depending on the combination of these two switches, the multilayer perceptron (MLP) model selects the appropriate operating mode. This may be charging mode, discharge mode, or battery protection mode against overcharge and deep discharge. Switch S_PG connects and disconnects the power generator, while switch S_G connects and disconnects the local network with the public network.

The critical operating scenarios that the system may encounter are: i) Protection against battery overcharging and deep discharge. This scenario arises when the power supplied by the photovoltaic module exceeds that required by the loads and the battery's state of charge reaches its maximum; ii) The second case occurs when the power supplied by the photovoltaic module is less than that required by the loads, and the battery's state of charge is at its minimum. The solution to this problem is for the MLP model to switch to the genset or public grid for powering the loads, recharge the battery from the genset or public grid, and protect the battery against overcharge; iii) Battery charging: this scenario arises when the power supplied by the photovoltaic module is higher than that required by the loads, but the battery's state of charge is lower than its maximum; and iv) Battery discharge: this scenario arises when the power supplied by the photovoltaic generator is below that required by the loads, but the battery's state of charge is above its minimum.

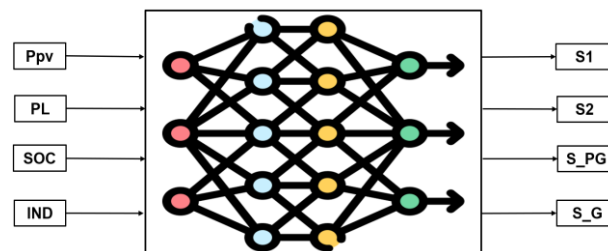


Figure 2. Multi-layer neural network

3. RESULTS AND DISCUSSION

This section consists of two distinct parts. The first part outlines and discusses the results of MLP model learning. While the second part presents the results of validating the reliability and robustness of the energy management model under different conditions of hybrid system operation.

3.1. Conception and optimization of energy management models

Deep neural networks are machine learning models with several layers of interconnected neurons. They are trained on large amounts of data, adjusting the weights of connections to achieve the desired outputs. Their recent success is attributed to algorithmic improvements, network architectures and the increased availability of data and computing power [15]–[18]. The use of deep neural networks on mobile and embedded devices poses challenges due to space and energy constraints. To optimize the MLP management model, a trial-and-error approach was used, adjusting parameters such as the number of layers and activation functions. This enabled us to find a configuration suited to the hardware constraints.

This section presents a summary of the optimal results obtained during the training, validation, and testing phases of the MLP model. For each loss function, we varied activation function of the hidden layer. The activation functions used are the logistic sigmoid activation function (L), the linear activation function (P) and the hyperbolic tangent activation function (T). The size of each training data vector consists of 60000 values. The data used for MLP training was divided into three parts: the first 70% of the data was used for training, the next 15% was used for the test phase and the last 15% was used in the validate phase for the MLP [19]–[21].

3.1.1. Learning results using mean absolute error

Table 1 summarizes the best MLP model learning results when using the mean absolute error (MAE) function as the loss function. As the table shows, with the combination of (Purelin, Logsig) activation functions and an architecture (4-9-4), the mean absolute error reaches a value of 56.459×10^{-3} at epoch 101, with the

combination of (Tansig, Logsig) activation functions and an architecture (4-11-4), the mean absolute error reaches a value of 38.904×10^{-3} at epoch 432 and with the combination of (Logsig, Logsig) activation functions and an architecture (4-8-4), the mean absolute error reaches a value of 16.790×10^{-3} at epoch 181.

Figure 3 shows the variation of the loss function in the training, the validation and the testing phases of the MLP model in relation to the number of epochs. The mean absolute error of the training, the validation and the testing phases reaches the value 16.790×10^{-3} an epoch 181, which indicates that we have convergence of the values predicted by the MLP model towards the desired values with an error equal to 16.790×10^{-3} . The graphs in Figure 3, showing that the learning, test and validation errors are almost identical, show that the MLP model has achieved a good level of generalization without falling into the problem of overlearning [22]–[25].

Table 1. Learning results using MAE

Hidden layer	Output layer	Labels	Architecture	MAE ($\times 10^{-3}$)	Number of epochs
Purelin	Logsig	PL	(4-9-4)	56.459	101
Tansig	Logsig	TL	(4-11-4)	38.904	432
Logsig	Logsig	LL	(4-8-4)	16.790	181

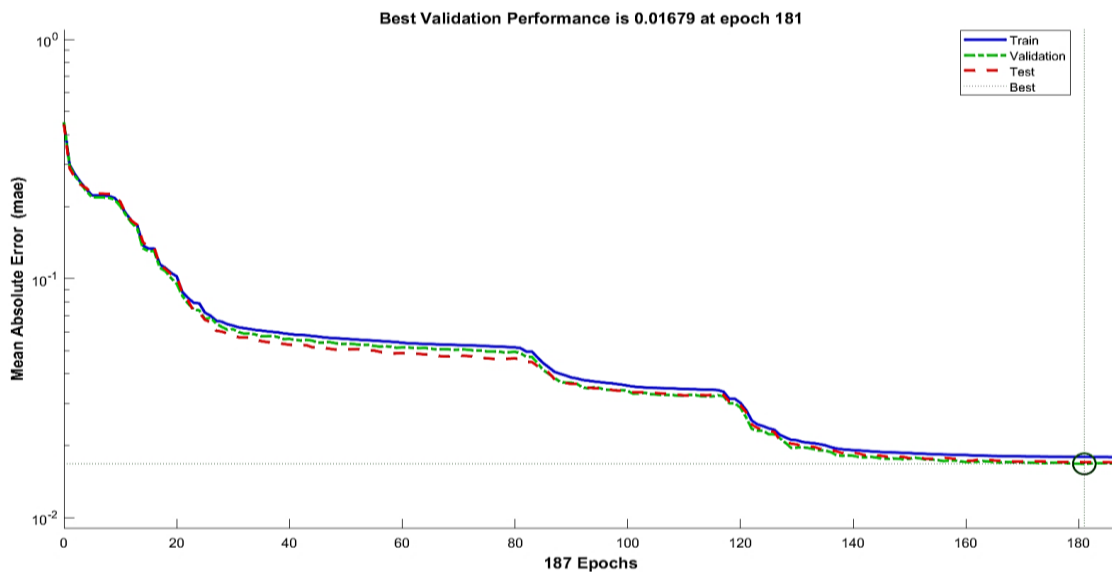


Figure 3. Learning performance using MAE

3.1.2. Learning results using mean squared error

Table 2 summarizes the best MLP model learning results when using the mean squared error (MSE) function as a loss function. As the table shows, with the combination of (Purelin, Logsig) activation functions and a (4-13-4) architecture, the mean square error reaches a value of $16,980 \times 10^{-3}$ at epoch 127, with the combination of (Tansig, Logsig) activation functions and a (4-8-4) architecture, the mean square error reaches a value of 7.366×10^{-3} in epoch 108, and with the combination of (Logsig, Logsig) activation functions and a (4-9-4) architecture, the mean square error reaches a value of 11.015×10^{-3} in epoch 199.

Figure 4 shows the variation of the loss function in the training, the validation and the testing phases of the MLP model in relation to the number of epochs. The mean absolute error of the training, the validation and the testing phases reaches the value 7.366×10^{-3} an epoch 108, which indicates that we have convergence of the values predicted by the MLP model towards the desired values with an error equal to 7.366×10^{-3} . The graphs in Figure 4, showing that the learning, test and validation errors are almost identical, show that the MLP model has achieved a good level of generalization without falling into the problem of overlearning.

Table 2. Learning results with MSE

Hidden layer	Output layer	Labels	Architecture	MSE ($\times 10^{-3}$)	Number of epochs
Purelin	Logsig	PL	(4-13-4)	16.980	127
Tansig	Logsig	TL	(4-8-4)	7.366	108
Logsig	Logsig	LL	(4-9-4)	11.015	199

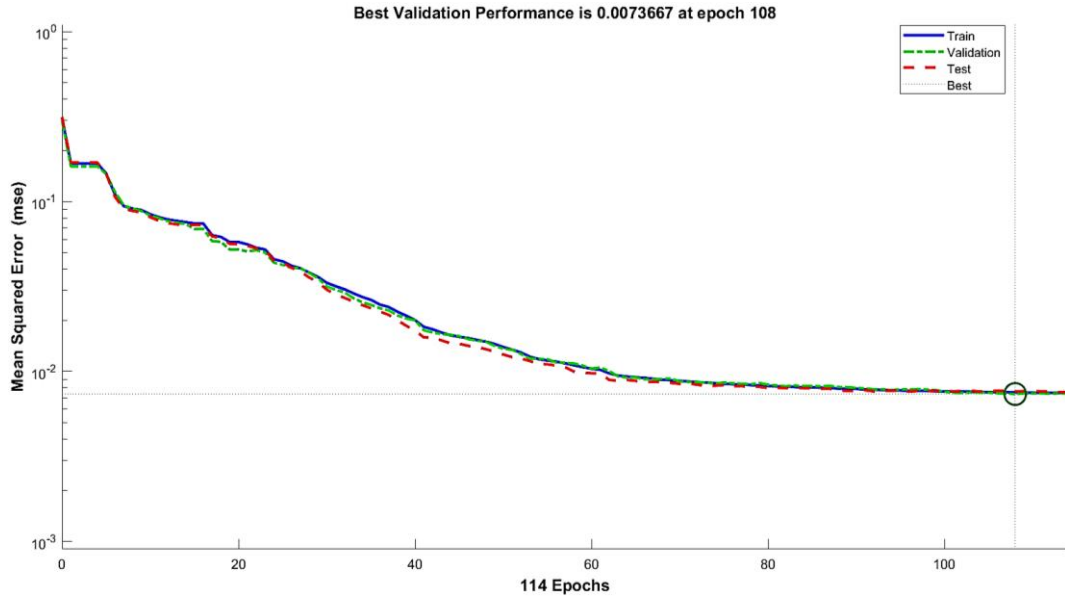


Figure 4. Learning performance using MSE

3.1.3. Learning results using cross-entropy

Table 3 summarizes the best MLP model learning results when using the cross-entropy (CE) function as a loss function. As the table shows, with the combination of (Purelin, Logsig) activation functions and a (4-9-4) architecture, the cross-entropy error reaches a value of 17.761×10^{-3} at epoch 91, with the combination of (Tansig, Logsig) activation functions and a (4-10-4) architecture, the cross-entropy error reaches a value of 9.051×10^{-3} in epoch 213, and with the combination of (Logsig, Logsig) activation functions and a (4-6-4) architecture, the cross-entropy error reaches a value of 8.965×10^{-3} in epoch 122.

Table 3. Learning results using cross-entropy

Hidden layer	Output layer	Labels	Architecture	CE ($\times 10^{-3}$)	Number of epochs
Purelin	Logsig	PL	(4-9-4)	17.761	91
Tansig	Logsig	TL	(4-10-4)	9.015	213
Logsig	Logsig	LL	(4-6-4)	8.965	122

Figure 5 shows the variation of the cross-entropy loss function in the training, the validation and the testing phases of the MLP model with the variation in the number of epochs. The results shown in this figure are obtained when using the (Logsig, Logsig) combination as the activation function. The cross-entropy error of the learning, test and validation phases arrives at the value 8.965×10^{-3} an epoch 122, which indicates that we have a convergence of the values returned by the MLP model towards the desired values with an error equal to 8.965×10^{-3} . The graphs in Figure 5, showing that the learning, test and validation errors are almost identical, show that the MLP model has achieved an excellent level of generalization without falling into the problem of overlearning.

3.1.4. Comparing learning results

Table 4 illustrates the better results achieved using the different loss functions and architectures. The lowest error value is achieved by using the cross-entropy function as a loss function and the logistic function as an activation function in the hidden and output layers. Figure 6 illustrates the MLP energy management model's optimized structure. It comprises three layers: there are four neurons in the input layer, four neurons in the output layer, and six neurons in the hidden layer.

Table 4. Comparison of the best results obtained in the three cases

Loss function	Labels	Architecture	Error ($\times 10^{-3}$)
MAE	LL	(4-8-4)	16.790
MSE	TL	(4-8-4)	7.366
Cross-entropy	LL	(4-6-4)	8.965

3.2. Validation of energy management model

This section analyses the effectiveness, resilience, and reliability of the MLP management model through different operational scenarios. Three critical situations may arise during power system operation, requiring immediate intervention to protect plant equipment and guarantee uninterrupted power to consumers. In order to verify and validate the performance and generalization of the MLP model developed, we put them in different function conditions. The test conditions are a variable power demand, a variable generated power and a battery state of charge below its minimum.

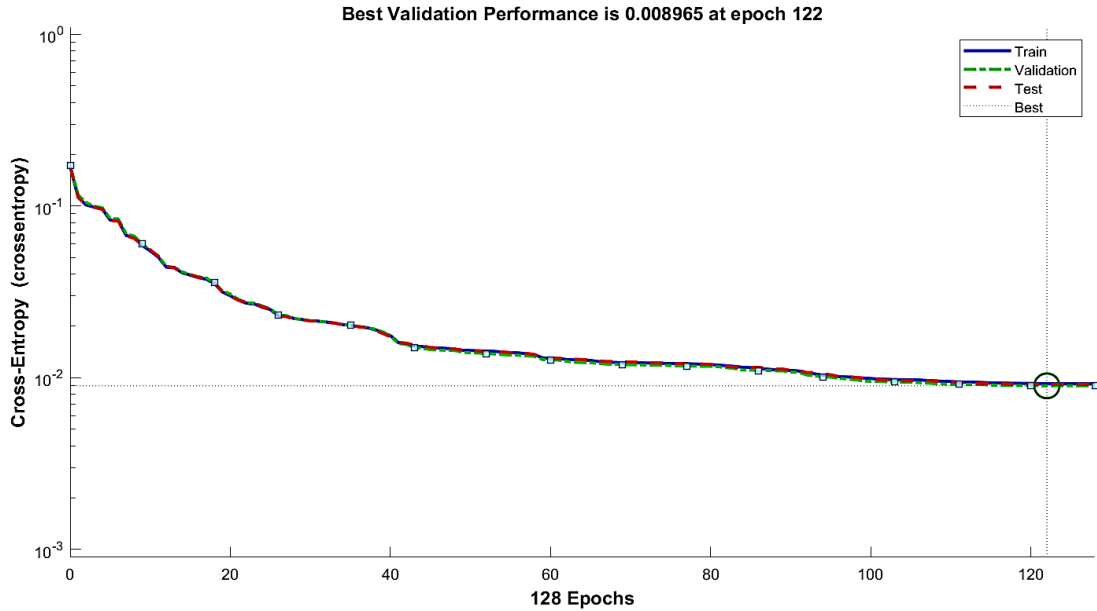


Figure 5. Learning performance using cross-entropy

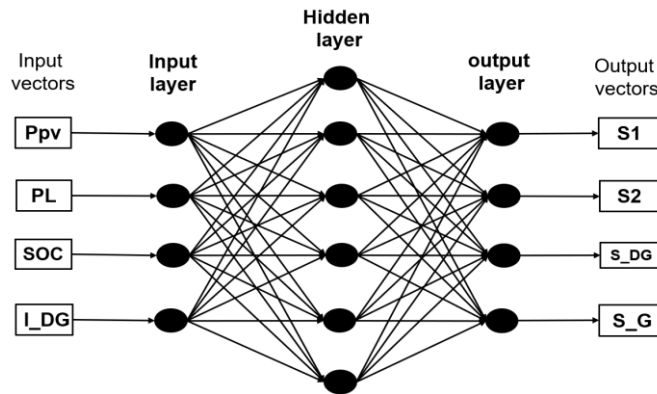


Figure 6. The MLP energy management model architecture

To analyze the results in the Figure 7, we'll take various critical time intervals and visualize the reaction and generalization of the management model. From 0 to 0.1 seconds, from 0.3 to 0.7 seconds, and from 0.9 to 1 second: during these time intervals, the output generated by the photovoltaic module is higher than the output required by the consumers, and the battery's state of charge is lower than its minimum. Consequently, the management model forces switch S2 to go to one and switch S1 to go to zero to ensure protection and charging of the battery from the photovoltaic generator. The status of the electricity generator and public grid connection switches remains unchanged, as the energy produced by the photovoltaic generator is enough to supply the consumers as well as charge the battery.

From 0.1 to 0.3 seconds: during this time interval, the output generated by the photovoltaic module has fallen below the power demanded by the loads, and the battery's state of charge is still below its minimum. To guarantee supply to the loads, the management model will check the operation of the generator, and since the generator operation indicator has been set to one, this means that the generator is capable of meeting the energy demand. Under these conditions, the management model makes the S2 switch go to one and the S1 switch go to zero to ensure battery protection and charging, but this time from the generator by setting the generator connection switch to one. The state of the switch for connection to the public grid remains unchanged, as local energy requirements are met by the power generator.

From 0.7 to 0.9 seconds: during this time interval, the output generated by the photovoltaic module has fallen below the power required by the loads, and the battery's state of charge is always below its minimum. To guarantee load supply, the management model will check the operation of the current generator, and as the generator operation indicator has been set to zero, this means that the current generator is unable to cover energy requirements. Under these conditions, the management model forces switch S2 to go to one and switch S1 to go to zero to ensure battery protection and charging, but this time from the public grid by setting the public grid connection switch to one.

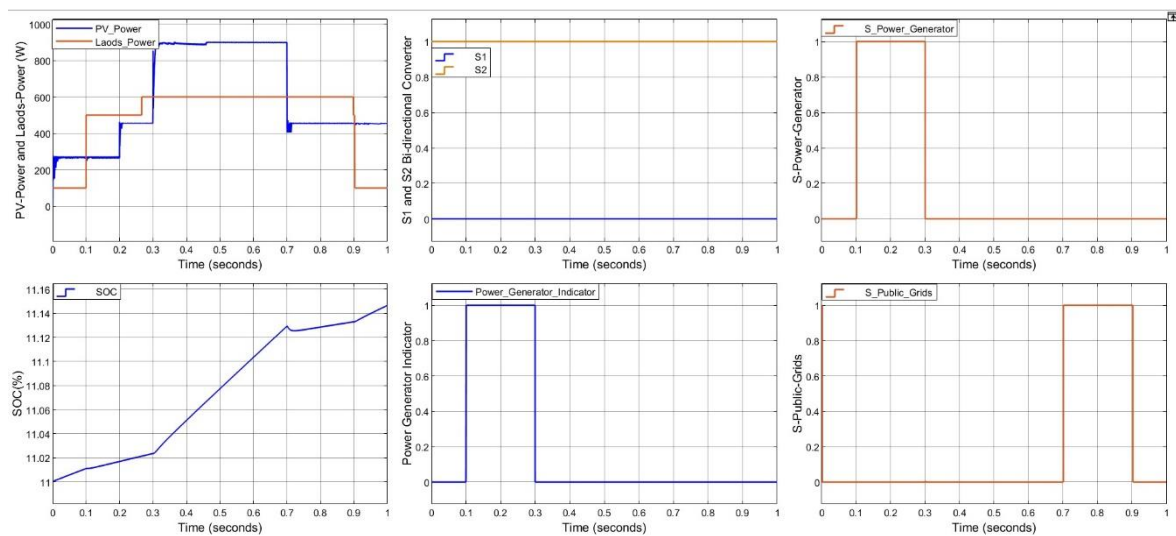


Figure 7. The operation of the MLP model in energy management

4. CONCLUSION

The implementation of a hybrid power generation system with decentralization and integration of storage units reduces dependence on fossil fuels and ensures a continuous power supply despite the variability of renewable energy sources. Incorporating safety considerations into the control system is recommended to ensure resilient and efficient performance. This article presents a control system based on an optimized multilayer neural network. It efficiently manages the battery's state of charge, provides protection against overcharging and deep discharge, and ensures the transition between different energy sources. As we have seen in the discussion section, the MLP model performs these functions effectively. The MLP model utilized in this research underwent a period of architecture optimization to minimize the number of parameters and computational requirements, hence enhancing ease of implementation. The MLP management model shown excellent performance across many operational situations inside the hybrid system.





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